VIBRATION DATA ANALYSIS FOR WORKER -LEVEL PRODUCTIVITY TRACKING IN CONSTRUCTION PROJECTS

A Thesis

by

KUN TAN

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Chair of Committee,	Eric Jing Du
Committee Members,	José L. Fernández-Solís
	Jim Ji
Head of Department,	Patrick Suermann

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ABSTRACT

The construction industry has been suffering from declining productivity since the 1950s. To tackle this issue, our industry has developed numerous productivity-tracking methods and systems. However, most of the existing tracking approaches focus on measuring work-level or team-level productivity. Some researchers have tried visual tracking with in-situ complexities or vibration data analysis for fall prediction. In this paper, we implemented vibration data analysis methods to efficiently track and identify ongoing construction action using vibration data. These data were collected from an accelerometer attached to power tools, representing 16 classes of construction actions frequently needed in pipeline work. We trained a support vector machine model and a decision tree model by feature matrixes and label matrixes generated from Y-axis values of raw data. We applied data preprocessing, frequency-domain feature extraction, training, 10-fold cross-validation, and parameter optimization. After cross-validation, results showed the support vector machine to have a better average accuracy result compared with the decision tree. Meanwhile, the support vector machine model successfully identified ongoing construction action. Overall, this research makes a significant contribution to applying machine-learning methods by vibration-data-processing techniques for tracking construction actions. In the future, construction managers can use this system to track and identify ongoing action on the site remotely, improving work efficiency and work-tracking robustness.

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CONTRIBUTORS AND FUNDING SOURCES

This work was supervised by a dissertation committee consisting of Dr. Eric Jing Du of the Department of Construction Science, Dr. José L. Fernández-Solís of the Department of Construction Science, and Dr. Jim Ji of the Department of Electronic Engineering.

The sensor with an accelerometer was designed by Li Zhe, a friend of Dr. Eric Jing Du. All other work conducted for the thesis was completed independently by the student Kun Tan under the advisement of Dr. Eric Jing Du.

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NOMENCLATURE

DT	Decision Tree
EVM	Earned Value Management
PPC	Percent Plan Complete
RBF	Radian Basis Function
RFID	Radio Frequency Identification
STFT	Short-time Fourier Transform
SVM	Support Vector Machine

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Background

Labor productivity in the construction industry has continued to decline since the 1970s, based on data from the United States Census Bureau (Allmon, Haas, Borcherding, & Goodrum, 2000; Pi, 2015). Although the construction industry has been striving to fix the problem in numerous ways, little improvement has been made. Literature has provided various plausible explanations for declining construction productivity. Our industry requires a better understanding of the solution to solve these productivity issues.

The construction is a labor-intensive industry. For a regular commercial project, it is common that hundreds of, or even, thousands of construction workers are involved. For example, more than 3,500 workers had worked on the 16-acre job site of the World Trade Center in New York City, totaling in 31 million man-hours from 2006 to 2014 (Smith, 2014). In the industrial sector, Tesla's Nevada Gigafactory requires 3,600 workers with 9.8 million man-hours during the construction of the 5-million-square-foot-facility (Archer, 2017). The labor-intensive nature makes it reasonable to contemplate that the productivity issue in the construction industry roots from the individual-level inefficiency. Given the increasing project complexity, project magnitude, and in-situ complexities on the job site, tracking the worker-level productivity can be even more challenging.

1.2 Problem Statement

Although overall productivity loss is caused at the individual level, existing productivity-tracking methods focus mostly on work-level or team-level performance tracking. For example, earned value management (EVM) quantifies accomplished works as a dollar amount and uses the ratio of planned work amount as an indicator of productivity. Individual-level information is missing in the EVM framework. The productivity of project management and supervision is very challenging, if not impossible, to measure and track thoroughly using work-level or team-level methods. So, there is an expanding gap between existing productivity-measurement and -tracking approaches and the labor-intensive nature of the construction industry. Because low-frequency human behavior tracking has been well studied, this paper focuses only on high-frequency construction actions.

To fill the gap, a system that tracks individual-worker-level productivity is urgently needed. The system should enable mapping from work packages to tradespeople. We find that vibration data analysis has the potential to facilitate individual-level measurement. Applying a sensor-orientated framework makes possible real-time data collection and interpretation of worker-level productivity tracking. Also, support vector machine (SVM) and decision tree methods help us to build models for tracking construction action.

1.3 Research Objectives

The goal of this paper is to explore a vibration data analysis framework for intelligent worker-level productivity tracking. Specifically, this research will accomplish two objectives:

1) **Collect vibration data attached to power tools and pre-process the data**: An experiment will be performed to collect sixteen kinds of power tools vibration data. Then, use STFT to expend the raw data and use feature extraction algorithm to get key components of construction actions (like an electric saw is sawing on a 1-1/4" PVC Pipe).

2) **Train and test SVM model and compare the result with Decision Tree model's result:** Train the SVM model and the DT model by 4 frequency domain features. Compare their cross-validation accuracy by 10-fold cross validation, testing accuracy by aggregate confusion matrixes. We also test and predict guarantee its validity and get SVM's parameter optimization result.

1.4 Hypothesis

Certain ongoing construction actions (like power tools drill with PVC pipe line) can be identified based on tools' vibration Y axis data.

1.5 Limitation

The discussed vibration data analysis in this study presents the following limitations that need to be addressed in the future:

1) The participant holding the power tools in this research is not professional construction workers, so the vibration data attached to power tools may not match exactly like the real construction work.
2) This research only tested a finite number of activities on a job site. Limited construction activities, tools, and materials are tested.

2. REVIEW OF LITERATURE

2.1 Current Productivity Control Method

2.1.1 Earned Value Management

EVM helps project control and can forecast final cost in the form of an EVM graphic. According to Fleming and Koppelman (2016), EVM methodology uses planned value, earned value, actual cost, and derived variances and indexes to make predictions. But Lipke, Zwikael, Henderson, and Anbari (2009) believed that EVM methods have provided no improvement since their development. They said that EVM might be applicable only to megaprojects with long durations. Although EVM is a remarkable achievement, a detailed, up-to-date productivity-control method is still an urgent need.

2.1.2 Individual Percent Plan Complete

Percent Plan Complete (PPC) is a measure calculated as the "number of promises" divided by the "total number of promises" (Institute, 2017). Hamzeh, Ballard, and Tommelein (2012) stated that "steps are tasks assigned to individuals within work groups." Forms of expression include weekly work plans and Gantt chart schedules. Project engineers present work plans weekly for review in staff meetings and post them on office doors. Ballard and Howell (1998) claimed that PPC enables production units to improve their productivity. But they also suggested that PPC is a clear and operational, but activity-based, lagging indicator for productivity control.

2.1.3 Radio Frequency Identification

Radio frequency identification (RFID) systems are a much-anticipated technology in the construction industry. Researchers tried to insert RFID tags within tool casings to test tools' location-tracking performance (Goodrum, McLaren, & Durfee, 2006). They presented that RFID can help in tracking and inventory systems originally used for storing operations. On the other hand, through field trials, the research identified poor economy, lack of standardization, and lack of directional data as RFID's disadvantages for commercialization. Although Montaser and Moselhi (2014) said that the tag price was only $5 in 2014, Sardroud (2012) confirmed that RFID in construction lacks training, knowledge, and ratified standards.

2.1.4 Visual Tracking

Some studies have focused on implementing image-processing methods to monitor construction productivity. For example, Computer Vision can be used to generate human poses on the jobsite (Peddi, Huan, Bai, & Kim, 2009). The researchers classified poses into three classes as effective work, ineffective work, and contributory work. Then, a built-in neural network was trained to determine the worker's status by comparing images to the developed human poses. However, Peddi's study was challenged by J. Gong and Caldas (2009). They claimed that the limitations of visual analysis cannot meet the needs of large-scale data analysis. So they trained a video interpretation model to convert construction operations into productivity information. Based on Hwangbo (2015)'s finding, visual tracking is limited by lighting conditions, viewing angles, and annoying calibration whenever the camera moves, leaving room for the opportunity of a better option.

2.1.5 Acoustic Tracking

Cheng, Rashidi, Davenport, and Anderson (2017) proposed an audio-based system for action identification of heavy construction equipment. The proposed system includes filtering, converting, classifying, and window filtering. The authors acknowledged that the system is only applicable for construction machines that generate discrete sound patterns (tower cranes and graders are not applicable). Further, the existence of sound barriers might affect performance.

Existing methods for productivity control have been summarized (Figure 1), leaving our study seeking to find an alternative way to perform detection.

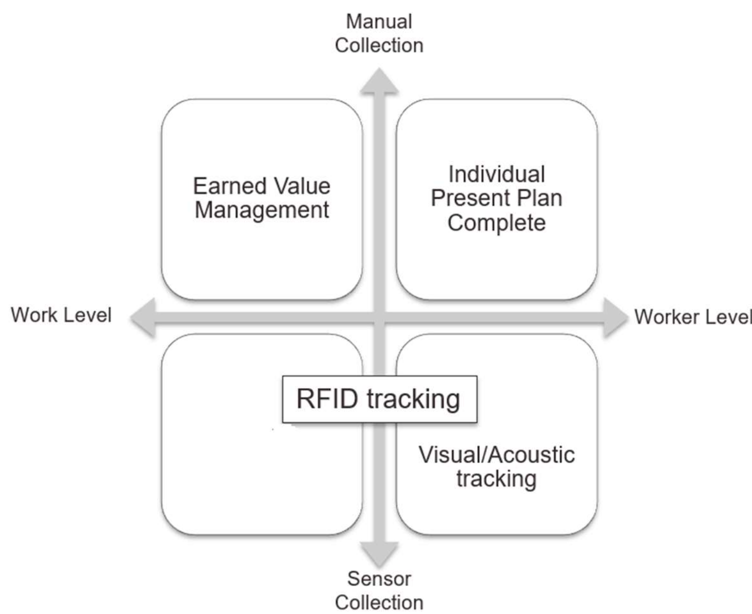

Figure 1 Existing Productivity Control Methods

2.2 Vibration Data Analysis

2.2.1 State of Arts of Vibration Data Analysis

Vibration data analysis is a complex integration of interdependent computational and physical processes. It connects the physical systems embedded with low-power wireless nodes to systems responsible for communication and control. E. A. Lee (2008)'s paper is one of the most cited in the vibration data analysis arena. Applications have also emerged like advanced electric power gridding (Rajkumar, Lee, Sha, & Stankovic, 2010) and machinery fault diagnosis (Liu, Liu, & Huang, 2011), etc. The National Science Foundation has announced that, in the future, it will pay more attention to shaping the human technology frontier (Mervis, 2016), including vibration data analysis.

2.2.2 Applications of vibration data analysis in Engineering

Vibration data analysis has been employed in structural health monitoring and energy monitoring. But there is no sufficient study focusing on worker-level productivity tracking. Hackmann et al. (2014) proposed a vibration data analysis approach for structural health monitoring based on wireless sensors. But due to the lack of real-time support, testing over long time scales cannot meet the challenges of dynamic systems. In response to this study, Huang et al. (2010) developed a data collection instrument for real-time power grid structural testing. Energy conservation is another application area. Modeling a building using vibration data analysis will play a critical role in achieving and operating zero-net-energy buildings. Smets, Eger, and Grenier (2010) did an experiment to test truck operators' traumatic injuries by vibration data analysis. From the above literature review, we found two facts related to our study: (1) vibration data analysis is popular in academia for solving item identification and tracking issues and (2) vibration data analysis for construction productivity tracking lacks studies, especially for actions generating high-frequency data like power-tool work (Table 1).

Table 1 Vibration Data Analysis in Engineering

Topic	Author	Year	Subject's Frequency(Hz)
Power grid structural testing	Huang et al.	2010	0-60
Driver's traumatic injuries prediction	Smets et al.	2010	1-4
Machinery fault diagnosis	Liu et al.	2011	107.4-162.2
Structural health monitoring	Hackmann et al.	2014	70-280
Worker's fall detection	Yang et al.	2016	3-51.2

According to some researchers (Hackmann et al., 2014; Yang, Ahn, Vuran, & Aria, 2016), when using a low-pass filter to process raw data, high frequency is defined as higher than 50 to 70 Hz. And considering that low-frequency human behavior tracking is already well studied (Smets et al., 2010; Yang et al., 2016), we only tested high-frequency construction actions like power tools.

2.2.3 Vibration Data Collection

Currently, smartphones and smartwatches already have accelerometers, but with deliberate frequency limitations for power saving. Laput, Xiao, and Harrison (2016) hacked an LG smartwatch and boosted the sampling rate of the smartwatch's accelerometer to 4 kHz. There is another way to identify objects and body motion: radar. A Google project named Soli(Yeo, Flamich, Schrempf, Harris-Birtill, & Quigley, 2016) used this chip and presented a portable, versatile, radar-based system for object classification. This research classified radar signals using a random forest classifier.

To assemble a small and obtainable sensor, Raspberry Pi® (Upton & Halfacree, 2014) might be a good choice. Compared with another single-chip microcomputer (Arduino®), Raspberry Pi can easily connect to the Internet with an entirely available Linux software stack (McFadden, 2018). For sensors, the accelerometer most widely used is Raspberry Pi (Banerjee, Sethia, Mittal, Arora, & Chauhan, 2013). Accelerometers are first introduced by Roylance and Angell (1979) (Table 2).

Table 2 Vibration Data Collection

Collection Method	Author	Year	Pros	Cons
Accelerometer	Roylance and Angell	1979	Small, Cheap	Single-use
Raspberry Pi	Banerjee et al.	2013	Small, Cheap, Bluetooth, Linux environment	Single-use
Radar chip	Yeo et al.	2016	Detect touchless gesture interactions	Expensive
Smartwatch	Laput et al.	2016	Multi-function	Expensive
Arduino	McFadden	2018	Support multiple sensors	Not easy to transfer data

They found that compared with other existing productivity-control methods, vibration data tracking supplied by Raspberry Pi and an accelerometer with a vibration-data-processing approach provides the following advantages (Table 2):

- There is no special limitation for accelerometers mounted on construction tools, while visual and RFID methods are not robust enough for a complex job site.
- Vibration data share fewer data rates than visual data.

- Raspberry Pi 3 is available in Bluetooth 4.1, is small enough to mount on tools, and is cheap enough to apply on a large scale for all tools on a site.
- Although there are some advanced sensors on the market that are smaller than Raspberry Pi + accelerometer, Raspberry Pi is the cheapest system that can implement collection and data transmission by Bluetooth to a laptop. And it has a Linus system, which makes writing code easy.

2.2.4 Data Processing

What kind of data analysis methods can help this study to reach the goal of identifying construction actions? After literature, we found that it must be a solution in Machine Learning area.

Moselhi, Hegazy, and Fazio (1991) first studied neural networks in the construction field. Tixier, Hallowell, Rajagopalan, and Bowman (2016) applied two algorithm models in injury prediction: Random Forest and Stochastic Gradient Tree Boosting. For accelerometer data processing, Yang et al. (2016) developed a method for automatically falls prediction among ironworkers. He used vibration data acquired from WIMUs attached to workers. He then trained a one-class support vector machine for near-miss fall detection. But his study is focusing on the step motion instead of construction action linked with tools or equipment. Joshua and Varghese (2010) evaluated classifiers including multilayer perceptron and neural network. They said the utilization of best features reduced the runtime considerably. Tomar and Agarwal (2013) make a detailed table indicating advantages and disadvantages of different classification techniques. For this study, we used SVM and DT as classifiers.

2.3 Support Vector Machine

The author analyzed data coming from accelerometers and identified what the ongoing construction action is. As mentioned in the literature review, this paper found out that Machine Learning might help in action recognition. It matches our purpose that inputting vibration data into a model can forecast a result.

2.3.1 Training and Testing

Within the Machine Learning world, Support Vector Machine (SVM), was first introduced in 1992 (Boser, Guyon, & Vapnik, 1992). It's one of Linear Classifiers, can separate different kinds of data points(Lin & Wang, 2002). To maximize the classification performance, researchers need to separate data as far or clear as possible.

After figuring out a proposed data processing method, this study tried to understand how to select training sets and testing sets to feed SVM (Guyon, Weston, Barnhill, & Vapnik, 2002). Generally, the goal of training sets is to generate a model who can forecast by inputting data and implementing algorithms, while testing sets are to get the accuracy rate as a standard to judge the model proper or weak. To solve Supervised Learning problems (Joachims, 1998), SVM is a classifier that needs training sets and testing sets under known labels. So, for this study, the vibration data analysis process can be divided into:

- Training Period. To summarize a model based on training sets and labels.
- Testing Period. To get an accuracy rate feedback based on the comparison between real construction action results and forecasting construction action results, generalized by the inputting of testing sets to the summarized model.

Within these two periods, validity(Cortes & Vapnik, 1995) and overfitting (Joachims, 1998) need to be noticed, which means the model obtained by training sets cannot generate ideal feedback after inputting testing sets.

2.3.2 Data Augmentation

Data Augmentation is widely used in Image Application whose methods include mirror, random cropping, rotation, and shearing(Ng, 2017); Parascandolo, Huttunen, and Virtanen (2016) were the first who introduced data augmentation in sound event detection by neural networks. They augmented the training set by transformations to reduce overfitting and to arise the dataset. They also gave readers three main segment of data augmentation in vibration data: Time stretching, Sub-frame time shifting, and Blocks mixing. In the last segment, overlapping blocks of the spectrogram are introduced.

2.3.3 Short-time Fourier Transform

Short-time Fourier Transform (STFT) is a method for analyzing a signal with frequency content changing over time (Fiebrink, 2009). Signal data is divided into small and overlapping frames. Before computing the STFT, the signal is multiplied by a window function. The windowing reduces the amplitude of the discontinuities at the boundaries of each finite sequence acquired by the digitizer. Researchers need to select a proper window function based on different kinds of signal contents. For vibration data, the Hanning window has good frequency resolution (National Instrument, 2016).

2.3.4 Feature Extraction

Then what is the training sets in this study? Under the context of SVM, they are feature vectors and matrix with labels. In machine learning, feature extraction helps raw data by deriving features to be more informative. Feature extraction is related to dimensionality reduction. The selected features are expected to contain the relevant information (A. Lee, 2018). Referred to Laput et al. (2016)'s work, this study selected statistical features including mean, max, min, and standard deviation.

2.3.5 Labeling

Since SVM needs training sets and testing sets under known labels, labeling is an inevitable step. Labels must be made by the author. In most cases, labeling is manually operated. Researchers can use MATLAB® tricks to generate a label matrix, but it's all based on their understanding of characteristics of experimental subjects. Carried forward by Russakovsky et al. (2015), they applied crowdsourcing in label images. That widened academics' eyes to put the labeling to a next level.

3. METHODOLOGY

3.1 Experimental Hardware

To collect power tools' vibration data, this study first planned to build devices combined with a small enough computer and a sensor to collect electronic power tools' vibration data. Raspberry Pi 3 is the natural choice for product selection. Besides the advantages described in the above literature review, it's also easier to find a supported sensor and tutorial online. In this study, we used an accelerometer costing $4 and manufactured by CJMCU Company; it can measure the biaxial inclination angle of the sensor and can detect the axis inclination angle change of both axes of the sensor (A. Gong, Wu, Qiu, & He, 2013). This accelerometer was bundled tightly with the tools. For the Linux setting of Raspberry Pi, the author set the sampling rate to 4 kHz (Laput et al., 2016). Considering Joshua and Varghese (2010) statement that the difference between wired or wireless devices affects the operator's motion, we chose Raspberry Pi 3 for its Bluetooth 4.1 feature. But because of time limitations, we used 40-pin Dupont wires to connect the board and the sensor, which gave us numerous troubles when an electronic power tool booted because the contact could have been lost. To overcome this problem, we added a breadboard to create conjunction (Figure 2).

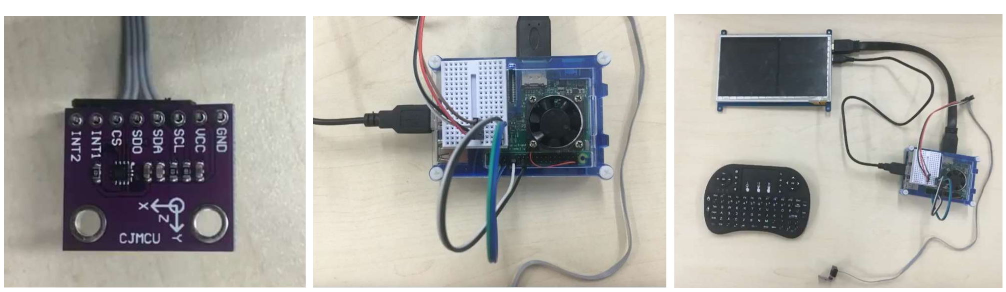

Figure 2 Accelerometer (Left); Raspberry Pi® 3 (Middle); The Whole Hardware System (Right)

3.2 Experimental Subject

3.2.1 Tools and Equipment

To illustrate clearly how to perform productivity control in the construction industry, we chose experimental subjects carefully. Peddi et al. (2009) took construction workers tying rebar as an example to perform worker tracking. J. Gong and Caldas (2009) took workers pouring concrete columns by crane-bucket as an example. Laput et al. (2016) tried everything from human gestures to manual saws. Because our goal was to track productivity at the worker level, power tools proved to be the best experimental subjects. They are widely used, are common to see on a job site, and are easily available for researchers. Because low-frequency vibration tracking is common today, the recognition of tools with high frequency needs further investigation (Laput et al., 2016).

3.2.2 Construction Actions

For the scenario, this study tried to simulate a piping project because although wood frame projects are the most common place to see electronic power tools, which is easy to collect high frequency vibration data. Another reason piping was chosen is that the piping process always happens in industrial construction, while wood frame frequently happens in residential construction, especially single-family-home construction, which is already well studied by existing productivity-control methods (Hendershott, Bosworth, & Jaffee, 1980). This paper selected 16 kinds of major actions in piping:

1) Drilling on a 0.5-ft-thickness vinyl tube, cordless drill
2) Drilling on a 0.75-ft-thickness PVC tube, cordless drill

3) Drilling on a1.5-ft-thickness PVC tube, cordless drill

4) Idle drill on high speed

5) Switching off the drill

6) Sawing on a 0.5-ft-thickness copper pipe, reciprocating saw

7) Sawing on a 0.75-ft-thickness PVC tube, reciprocating saw

8) Sawing on 1.5-ft-thickness PVC tube, reciprocating saw

9) Drilling on 2- × 2- × 8-ft lumber, cordless drill

10) Sawing on 2- × 2- × 8-ft lumber, compound miter saw

11) Sawing on 1.5-ft-thickness PVC tube, compound miter saw

12) Sawing on 0.75-ft-thickness PVC tube, compound miter saw

13) Polishing on 2- × 2- × 8-ft lumber, belt sander

14) Polishing on 1.5-ft-thickness PVC tube, belt sander

15) Sawing on 2- × 2- × 8-ft lumber, band saw

16) Sawing on 0.75-ft-thickness PVC tube, band saw

The models of power tools used were Makita 18-V Cordless Drill #LXPH03, Makita Electronic Reciprocating Saw #JR3070CT, Makita 15-Amp, 12-in., Corded Double Bevel Sliding Compound Miter Saw (Figure 3), Powermatic Belt and Disc Sander Combo Machine 1.5 HP, and Tannewitz 36-in. Band Saw (Figure 4).

Figure 3 Makita Compound Miter Saw (Left); The Attached Sensor (Right)

Figure 4 Powermatic Belt Sander (Left); Tannewitz 36″ Band Saws (Right)

3.3 Experimental Process

3.3.1 Data Collection

This study designed an indoor experiment at Langford C Woodshop, College Station, Texas, on June 1, 2018. 16 segments of construction actions in the same location were performed by the author. The accelerometer was fastened on the top of saws and drills using duct tape. The author tried each time to keep the power tool perpendicular to the ground to make the accelerometer's Y-axis perpendicular to the ground. Each action lasted around 13 seconds while drilling and sawing smoothly and slowly. The setup process for data collection is depicted in Fig 5. We configured the sensor to transmit all captured vibration data via Google Drive in the Linux system relayed to a laptop for analysis. Since Raspberry Pi 3 has the Bluetooth 4.1 feature, a rapid analysis and testing applications might work for future study.

Figure 5 Setup Process for Vibration Data Collections Using an Accelerometer and a Raspberry Pi®(Left); Keep the Sensor and Power Tool Perpendicular to the Ground(Right).

3.3.2 Data Processing—Support Vector Machine

After the data collection, the standard process of SVM was followed: data processing, training, and testing (Plaza et al., 2009). First, the author only extracted the Y-axis data, which were perpendicular to the ground and parallel to the power tools. Then, referring to Cheng, Rashidi, Davenport, and Anderson (2016)'s setting for data processing, time domain data were converted to frequency-domain data using the Short-Time Fourier Transform (STFT) with MATLAB®. The author used the Hanning window with size 512, 1024-point STFT, and 50% overlap (Sabillon, 2017) because the Hanning window is especially suitable for a narrowband, random signal like vibration (National Instrument, 2016). The Hanning window is a discrete window function in digital signal processing to select a series of samples to implement STFT. The advantage of the Hanning window is very low aliasing, and the tradeoff is slightly decreased resolution.

Our article tested data augmentation practices to solve potential overfitting issues in the SVM classification with 50% overlapped frames. We picked up 16 extra frames to cover more time domains. So, one frame for 16 kinds of construction action was augmented to 10 frames. But we only selected every two samples as training sets, leaving the rest to be the testing set. The question of identification of construction actions was simplified into a question about training a nine-category classifier with 90 samples (each with four features).

To identify construction actions, we started to train an SVM classifier. The LIBSVM MATLAB package was used for this task (Chang & Lin, 2011). We used the radial basis function (RBF) kernel for SVM. The label matrix was generated, along with the training sets. Once the SVM was trained by feature vectors and the matrix was given labels, we did not follow

10-fold cross-validation, but still used the frame of each action as the testing set. The label matrix was generated along with the training sets (Table 3).

Table 3 Data Processing Steps

3.3.3 Data Processing—Decision Tree

A decision tree is a decision support tool that uses a tree-like model of decisions (Basic Knowledge 101, 2018). Decision tree learning uses a decision tree to go from observations about an item to conclusions about the item's target value (Dimitrios, 2017). MATLAB Statistics and Machine Learning Toolbox are suitable for training a binary classification decision tree for multiclass classification (Beygelzimer, Langford, & Ravikumar, 2007).

4. RESULTS AND DISCUSSION

This section presents results and discusses them in two parts: (1) SVM and decision tree accuracy results and (2) results comparison and how to improve accuracy. We used LIBSVM, Statistics and Machine Learning Toolbox, and MATLAB R2014a. The notebook the author used was ThinkPad W540, Intel® Core (TM) i7-4800MQ CPU @ 2.70 GHz with 12-GB RAM.

4.1 Support Vector Machine Results

Based on the data-processing method mentioned in the last section, the SVM was trained by the Y-axis of accelerometer vibration data. This SVM was a one-versus-one classifier with an equal Hanning window and an RBF kernel.

The raw data for the 16 segments are depicted in Fig 6. Note that the x-axis is plotted in log-scale, from 10 Hz to 1 kHz. As shown in Fig 6, a wide range of recognized object characters fell well beyond the 10-Hz range. The X-axis presents time samples. The Y-axis presents noncentralized acceleration. Considering tools were not keep touching materials during the time domain, we selected points from 25,000 to 26,024 for actions #1, #3 and #9. We selected points from 45,000 to 46,024 for action #2's training sets to better represent this action's features. Fig 7 shows the results of each action implementing the Hanning window function to a 512-size, 1024-point STFT with a 50% overlap (256 overlapped samples). The X-axis represents frequency (Hz) (plotted in log-scale), and the Y-axis represents amplitude. When the power tool was off, there was no main frequency. And a wide range of characteristic object oscillations fell between 10 and 500 Hz.

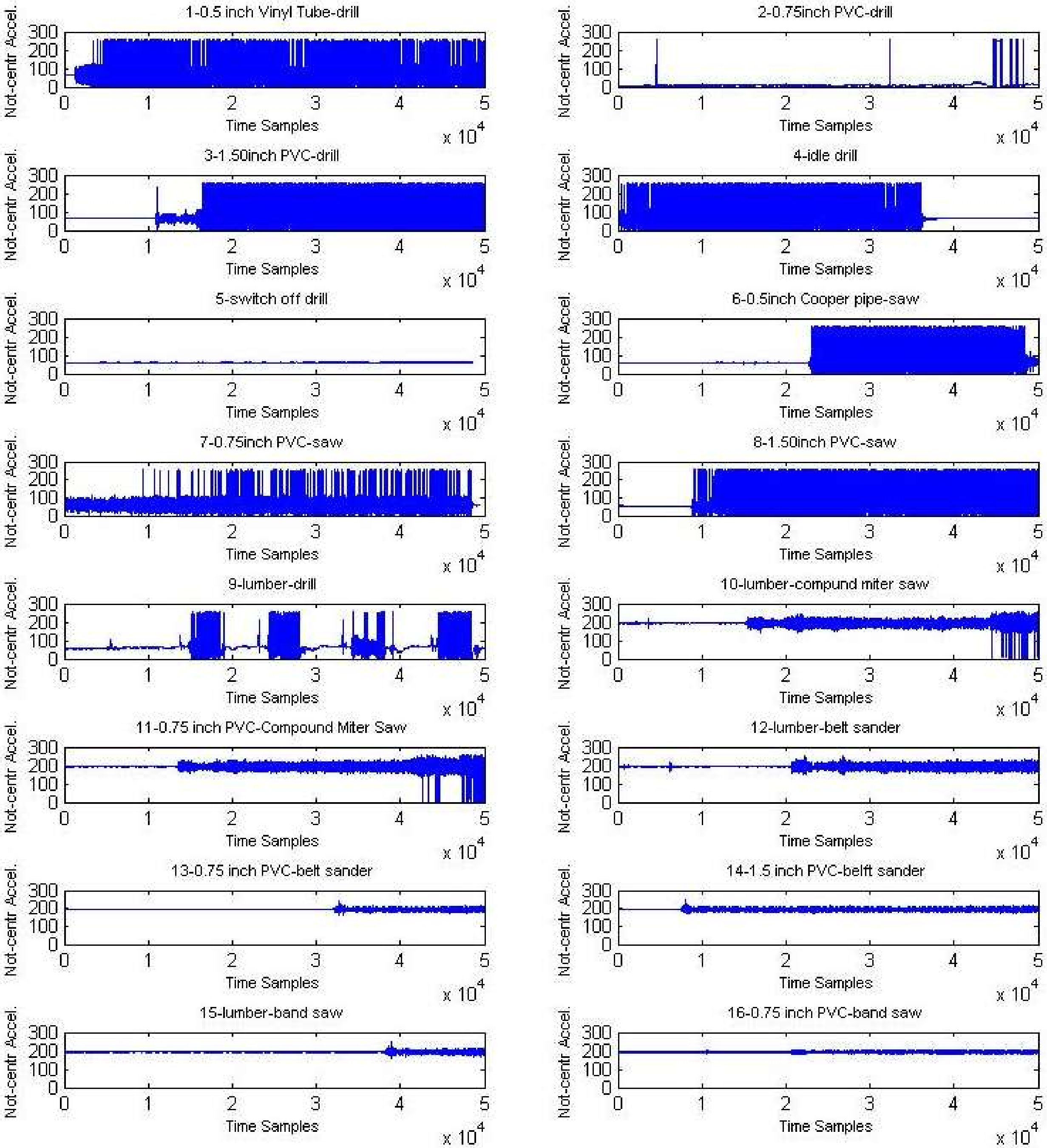

Figure 6 Raw Data

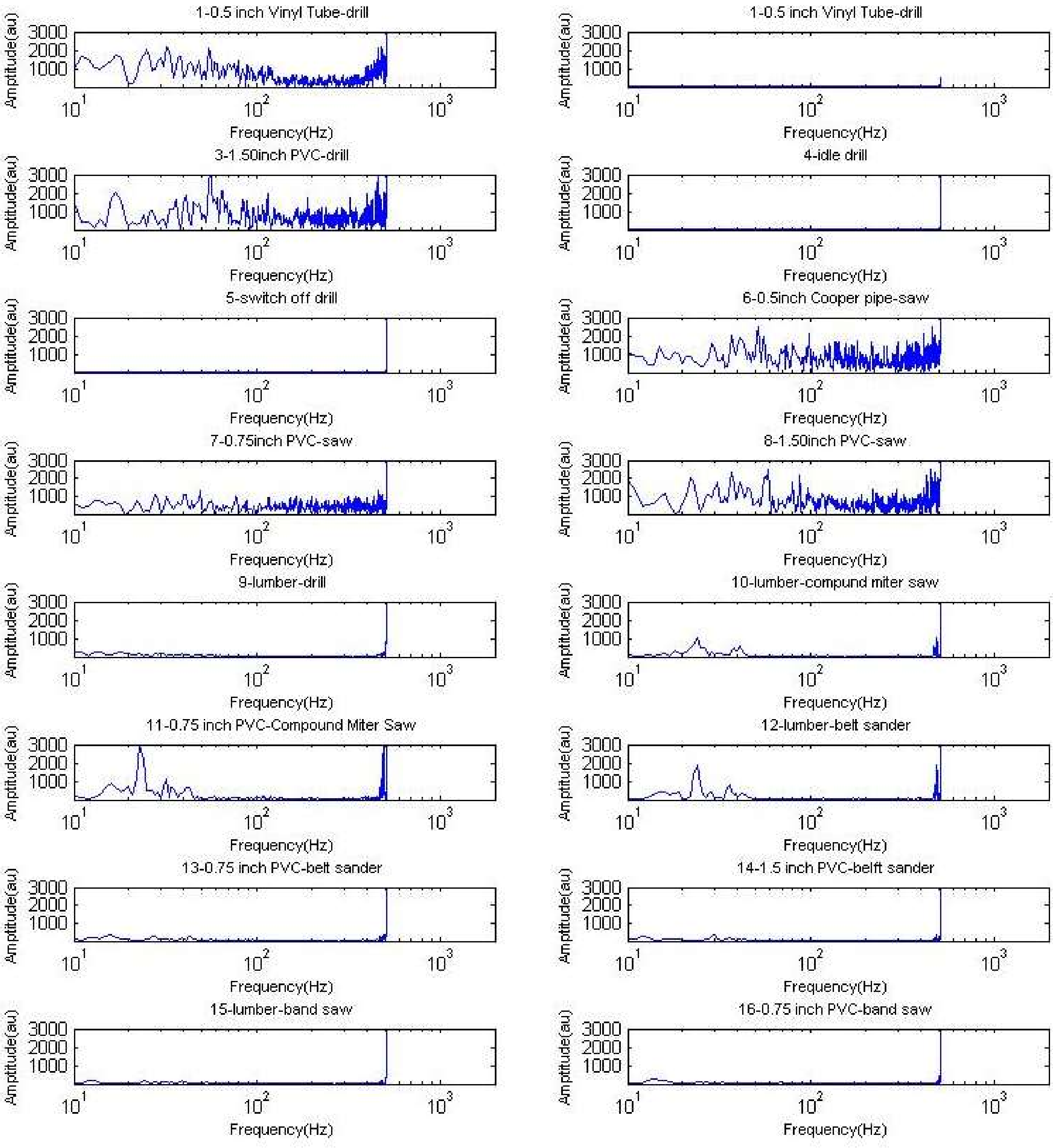

Figure 7 After STFT

To evaluate the performance of a machine-learning method, we made aggregate confusion matrixes after each test. A confusion matrix is a table describing the performance of a classifier on a testing set from the true values that are known. There are some basic terms to describe a confusion matrix:

- True positive (TP): We predicted yes (they have the disease), and they do have the disease.
- True negative (TN): We predicted no, and they don't have the disease.
- False positive (FP): We predicted yes, but they don't have the disease.
- False negative (FN): We predicted no, but they do have the disease.

And normally we describe the accuracy in the Formal 1.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN) \quad (1)$$

Figure 8 shows an aggregate confusion matrix describing all of the 10-fold cross-validation results; the average of these results was 58.125% (93/160). After parameter optimization (best c = 512, best gamma = 0.125), the accuracy of our SVM model came to 63.125%. Therefore, it was proved that the data analysis designed by this study successfully classified the 16 proposed construction actions.

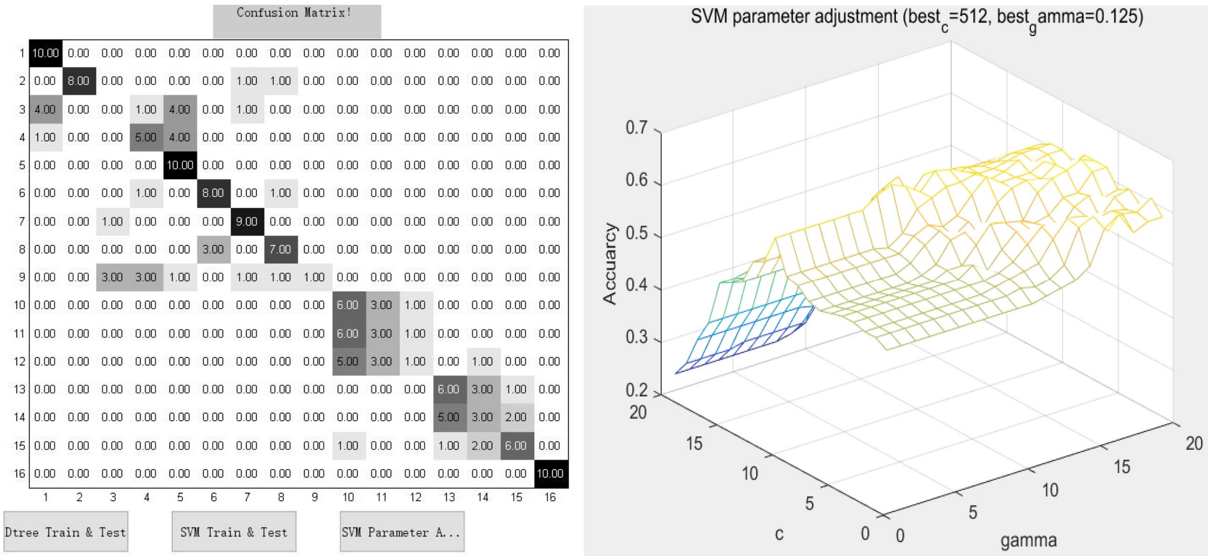

Figure 8 Confusion Matrix Result of SVM After Cross Validation (Left); SVM Parameter Adjustment (Right)

After testing the reliability of the trained classifier, we picked up an unlabeled dataset from action #2 that did not belong to previous training sets or testing sets. When we input this set, the proposed model answered: “What is the ongoing construction action? The answer is 2.” A classification chart was generated showing the prediction accuracy at up to 80% (as shown in Figure 9).

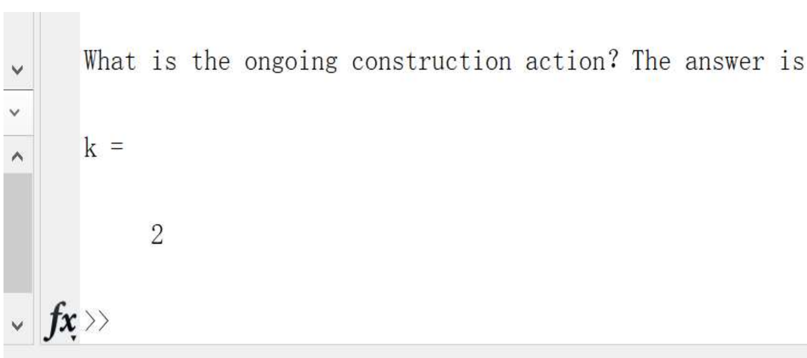

Figure 9 The Successful Classification Makes the VDA a Closed Loop.

4.2 Decision Tree Results

Using the same training set and testing set, we created a classification tree in MATLAB R2014a. Fig 10 is an aggregate confusion matrix describing all the 10-fold cross-validation results; the average of these results was 57.5% (92/160), which is lower than SVM's accuracy after cross-validation (58.125%).

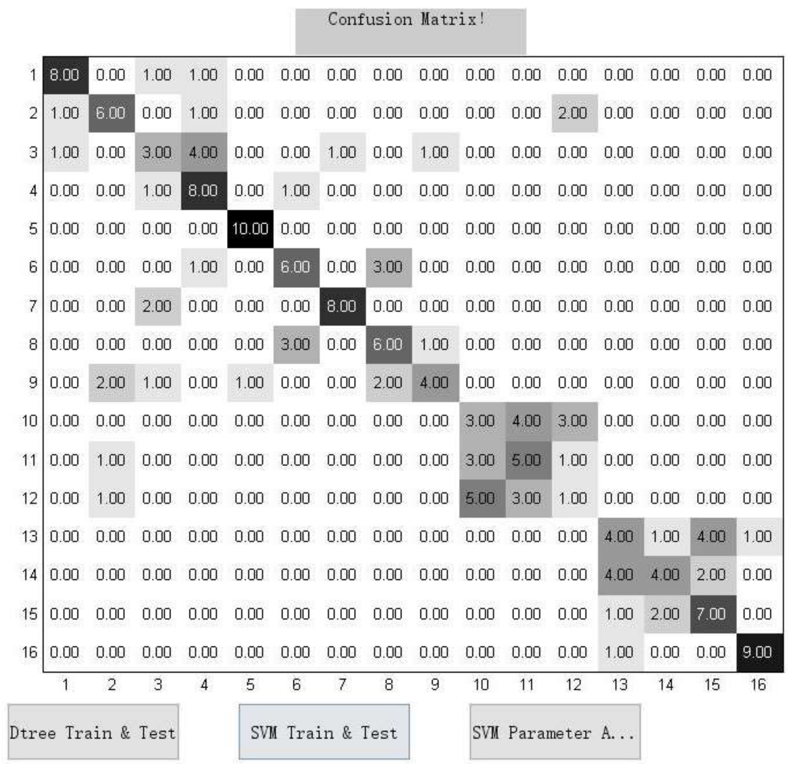

Figure 10 Confusion Matrix Result of Decision Tree After Cross Validation

4.3 How to Improve the Accuracy

In this study, we collected 16 classes of construction actions, each with 10 sample sets. We set power tools to touch different materials of different sizes in a pipeline work environment. The limited number of samples may affect our study's accuracy. For further study, more different subjects and more trial times can be tested.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

This study served to achieve a milestone toward a closed-loop construction productivity-control method by introducing vibration data analysis. The author developed a Raspberry Pi system with an accelerometer attached to collect vibration signals. Next, we trained SVM and decision tree models in 16 classes of construction actions with toolboxes in MATLAB R2014a. After the 10-fold cross-validation, SVM's average accuracy was 58.125%, and the decision tree's average accuracy result was 57.5%. After parameter optimization, SVM showed 63.125% (best c = 512, best gamma = 0.125). The result justifies our hypothesis that our model can identify ongoing construction action after entering an unknown dataset.

In short, this research makes two major contributions to advancing the construction industry. First, advanced vibration data analysis can help construction managers to track ongoing action remotely. Second, our study shows that in a finite training dataset, SVM can reach a high testing accuracy before cross-validation, while the decision tree model may have a higher accuracy than SVM after 10-fold cross-validation. Further study may include construction identification associated with P6 API to determine a worker's schedule performance.

5.2 Recommendations for Future Work

Future work could focus on improving the validity and robustness of the growing complex industry.

1) Currently, the participant holding power tools is not a professional construction worker. In the future researches could be performed on a real job site with more noises and in a more realistic construction action.
2) In the reality application, we believe that each tool attached with a sensor is achievable, while the Raspberry Pi® is not small enough to carry with all around the jobsite. So this study is trying to start a discussion of implementing vibration sensors on invidual-level productivity tracking. If someone wants to commercialize it, we do need a smaller device which can take the role of transfering the data from the sensor to our laptop by Bluetooth.
3) The real-time application interconnected with P6 API data to determine "behind of schedule", "on time", and "ahead of schedule" is still needed to be explored.

REFERENCES

Allmon, E., Haas, C. T., Borcherding, J. D., & Goodrum, P. M. (2000). US construction labor productivity trends, 1970–1998. *Journal of Construction Engineering and Management, 126*(2), 97-104.

Archer, S. (2017). BAIRD: Tesla's Gigafactory is ramping up — and it hands the carmaker a huge advantage (TSLA). *Bussiness Insider*.

Ballard, G., & Howell, G. (1998). Shielding production: essential step in production control. *Journal of Construction Engineering and Management, 124*(1), 11-17.

Banerjee, S., Sethia, D., Mittal, T., Arora, U., & Chauhan, A. (2013). *Secure sensor node with Raspberry Pi.* Paper presented at the Multimedia, Signal Processing and Communication Technologies (IMPACT), 2013 International Conference on.

Basic Knowledge 101. (2018). Problem Solving. Retrieved from http://www.basicknowledge101.com/subjects/problemsolving.html

Beygelzimer, A., Langford, J., & Ravikumar, P. (2007). Multiclass classification with filter trees. *Preprint, June, 2*.

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). *A training algorithm for optimal margin classifiers.* Paper presented at the Proceedings of the fifth annual workshop on Computational learning theory.

Chang, C.-C., & Lin, C.-J. (2011). LIBSVM: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST), 2*(3), 27.

Cheng, C.-F., Rashidi, A., Davenport, M. A., & Anderson, D. (2016). *Audio Signal Processing for Activity Recognition of Construction Heavy Equipment.* Paper presented at the ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction.

Cheng, C.-F., Rashidi, A., Davenport, M. A., & Anderson, D. V. (2017). Activity analysis of construction equipment using audio signals and support vector machines. *Automation in Construction, 81*, 240-253.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning, 20*(3), 273-297.

Dimitrios, P. (2017). design and development of a cognitive data analytics engine for network security, implementing Big Data technologies & machine learning techniques

Fiebrink, R. (2009). FFT/STFT cheat sheet. Retrieved from http://www.cs.princeton.edu/~fiebrink/314/2009/week12/FFT_handout.pdf

Fleming, Q. W., & Koppelman, J. M. (2016). *Earned value project management*.

Gong, A., Wu, X., Qiu, Z., & He, Y. (2013). A handheld device for leaf area measurement. *Computers and electronics in agriculture, 98*, 74-80.

Gong, J., & Caldas, C. H. (2009). Computer vision-based video interpretation model for automated productivity analysis of construction operations. *Journal of Computing in Civil Engineering, 24*(3), 252-263.

Goodrum, P. M., McLaren, M. A., & Durfee, A. (2006). The application of active radio frequency identification technology for tool tracking on construction job sites. *Automation in Construction, 15*(3), 292-302.

Guyon, I., Weston, J., Barnhill, S., & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine learning, 46*(1-3), 389-422.

Hackmann, G., Guo, W., Yan, G., Sun, Z., Lu, C., & Dyke, S. (2014). Cyber-physical codesign of distributed structural health monitoring with wireless sensor networks. *IEEE Transactions on Parallel and Distributed Systems, 25*(1), 63-72.

Hamzeh, F., Ballard, G., & Tommelein, I. D. (2012). Rethinking Lookahead Planning to Optimize Construction Workflow. *Lean Construction Journal*.

Hendershott, P. H., Bosworth, B. P., & Jaffee, D. M. (1980). Real user costs and the demand for single-family housing. *Brookings Papers on Economic Activity, 1980*(2), 401-452.

Huang, H.-M., Tidwell, T., Gill, C., Lu, C., Gao, X., & Dyke, S. (2010). *Cyber-physical systems for real-time hybrid structural testing: a case study.* Paper presented at the Proceedings of the 1st ACM/IEEE international conference on cyber-physical systems.

Hwangbo, H. (2015). The capabilities and limitations of video analytics.

Institute, L. C. (2017). LCI Lean Project Delivery Glossary.

Joachims, T. (1998). *Text categorization with support vector machines: Learning with many relevant features.* Paper presented at the European conference on machine learning.

Joshua, L., & Varghese, K. (2010). Accelerometer-based activity recognition in construction. *Journal of Computing in Civil Engineering, 25*(5), 370-379.

Laput, G., Xiao, R., & Harrison, C. (2016). *Viband: High-fidelity bio-acoustic sensing using commodity smartwatch accelerometers.* Paper presented at the Proceedings of the 29th Annual Symposium on User Interface Software and Technology.

Lee, A. (2018). Feature Extraction. Retrieved from http://saili.science/2017/05/10/feature-extraction/

Lee, E. A. (2008). *Cyber physical systems: Design challenges.* Paper presented at the Object oriented real-time distributed computing (isorc), 2008 11th ieee international symposium on.

Lin, C.-F., & Wang, S.-D. (2002). Fuzzy support vector machines. *IEEE transactions on neural networks, 13*(2), 464-471.

Lipke, W., Zwikael, O., Henderson, K., & Anbari, F. (2009). Prediction of project outcome: The application of statistical methods to earned value management and earned schedule performance indexes. *International journal of project management, 27*(4), 400-407.

Liu, H., Liu, C., & Huang, Y. (2011). Adaptive feature extraction using sparse coding for machinery fault diagnosis. *Mechanical Systems and Signal Processing, 25*(2), 558-574.

McFadden, C. (2018). Raspberry Pi and Arduino: What's the Difference and Which Is Best for Your Project?

Mervis, J. (2016). NSF director unveils big ideas, with an eye on the next president and Congress. *Science.* Retrieved from http://www.sciencemag.org/news/2016/05/nsf-director-unveils-big-ideas-eye-next-president-and-congress

Montaser, A., & Moselhi, O. (2014). RFID indoor location identification for construction projects. *Automation in Construction, 39*, 167-179.

Moselhi, O., Hegazy, T., & Fazio, P. (1991). Neural networks as tools in construction. *Journal of Construction Engineering and Management, 117*(4), 606-625.

National Instrument. (2016). Understanding FFTs and Windowing Retrieved from http://download.ni.com/evaluation/pxi/Understanding%20FFTs%20and%20Windowing.pdf

Ng, A. (2017). Data Augmentation. Retrieved from https://www.coursera.org/learn/convolutional-neural-networks/lecture/AYzbX/data-augmentation
Parascandolo, G., Huttunen, H., & Virtanen, T. (2016). *Recurrent neural networks for polyphonic sound event detection in real life recordings.* Paper presented at the Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on.
Peddi, A., Huan, L., Bai, Y., & Kim, S. (2009). *Development of human pose analyzing algorithms for the determination of construction productivity in real-time.* Paper presented at the Construction Research Congress 2009: Building a Sustainable Future.
Pi, R. (2015). Raspberry Pi Model B. In.
Plaza, A., Benediktsson, J. A., Boardman, J. W., Brazile, J., Bruzzone, L., Camps-Valls, G., . . . Gualtieri, A. (2009). Recent advances in techniques for hyperspectral image processing. *Remote sensing of environment, 113*, S110-S122.
Rajkumar, R. R., Lee, I., Sha, L., & Stankovic, J. (2010). *Cyber-physical systems: the next computing revolution.* Paper presented at the Proceedings of the 47th design automation conference.
Roylance, L. M., & Angell, J. B. (1979). A batch-fabricated silicon accelerometer. *IEEE Transactions on Electron Devices, 26*(12), 1911-1917.
Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., . . . Bernstein, M. (2015). Imagenet large scale visual recognition challenge. *International Journal of Computer Vision, 115*(3), 211-252.
Sabillon, C. A. (2017). Audio-Based Productivity Forecasting of Construction Cyclic Activities.
Sardroud, J. M. (2012). Influence of RFID technology on automated management of construction materials and components. *Scientia Iranica, 19*(3), 381-392.
Smets, M. P., Eger, T. R., & Grenier, S. G. (2010). Whole-body vibration experienced by haulage truck operators in surface mining operations: a comparison of various analysis methods utilized in the prediction of health risks. *Applied Ergonomics, 41*(6), 763-770.
Smith, G. B. (2014). EXCLUSIVE: Dozens of injuries at World Trade Center construction site went unreported. *NEW YORK DAILY NEWS.* Retrieved from http://www.nydailynews.com/new-york/exclusive-dozens-injuries-wtc-site-unreported-article-1.1996945
Tixier, A. J.-P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2016). Application of machine learning to construction injury prediction. *Automation in Construction, 69*, 102-114.
Tomar, D., & Agarwal, S. (2013). A survey on Data Mining approaches for Healthcare. *International Journal of Bio-Science and Bio-Technology, 5*(5), 241-266.
Upton, E., & Halfacree, G. (2014). *Raspberry Pi user guide*: John Wiley & Sons.
Yang, K., Ahn, C. R., Vuran, M. C., & Aria, S. S. (2016). Semi-supervised near-miss fall detection for ironworkers with a wearable inertial measurement unit. *Automation in Construction, 68*, 194-202.
Yeo, H.-S., Flamich, G., Schrempf, P., Harris-Birtill, D., & Quigley, A. (2016). *Radarcat: Radar categorization for input & interaction.* Paper presented at the Proceedings of the 29th Annual Symposium on User Interface Software and Technology.